A Web-based CBR Agent for Financial Forecasting

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Abstract

This paper presents a Web-based case-based reasoning model to assist investors to determine stock trend signals for investment in stock business. The model conforms to a Web-based agent framework forming part of an advisory system for financial forecast. Much of the discussion will be devoted to the design and development of the framework and associated intelligent techniques. Different cases are collected based on the theory of waves features and their combinations. The agent framework supports processes including Knowledge generation, Wave units mining and Wave Pattern recognition, and Case Revise and Learning. Preliminary result indicates that the CBR agent model is promising and reasonable. It is feasible to capture the trading behavior of the market with expandable case options.

Keywords: Web-based system, CBR agent, financial forecasting

1. Introduction

Financial market in Hong Kong is a very active market. The average daily turnover of the stock market (Main Board and Growth Enterprise Market) during 2000 was HK$12.7 billion. With a total market capitalisation of HK$4, 862 billion then, Hong Kong was the 11th largest stock exchange in the world and the 2nd in Asia [2, 3].

Many citizens participate in investing money on stocks. The Hong Kong Exchanges and Clearing Limited conducted a survey on stock market retail investor participation between November and December 2000 [1]. According to the survey's findings, about 21% of the Hong Kong adult population (i.e. 1,147,000 individuals) were stock investors. In order to make a profit from the market, investors follow one simple rule: "Buy low, sell high". Although this rule is simple and well known, it is difficult to follow. It is because the trend of the market is influenced by many factors (such as political and economical factors) and on the other hand, the market itself influences these factors. Various market analysis techniques are applied to interpret the status of the market and predict the market's future trend, but they are not beneficial to small investors because these techniques require certain degree of expertise in finance and economics. In addition, these techniques require extensive data collection about the market and many calculations, which is too much effort for individual small investors. Therefore, an advisory tool using these techniques is very useful for small investors to make trading decisions.

Moreover, world-wide-web provides a means for the users to retrieve information from any web sites all over the world, regardless of where the users are located. It can be a basis for uniform information distribution, independent of how you store information. Diffusion can thus rely on populating knowledge elements on the Web or on a knowledge server on the Web (Corby and Dieng, 1999). Unfortunately, our tools for locating, filtering, and analysing that information have not kept pace. E-commerce applications face challenges that intelligent techniques and the adoption of agent technology (Klusch, 1999; Lee and Liu, 2000b; 2000c; 2000d; Liu and You, 2000) may overcome. The intelligent techniques include the use of fuzzy logic for knowledge representation and make useful inferences or actions, expert systems for evidential and heuristics reasoning (Liu, 2001), neural networks for classification and adaptive learning (Lee and Liu, 2000a; 2000b; Kamijo, 1990), genetic algorithms for solution optimisation (Lee and Liu, 2000c), and data mining techniques for knowledge discovery (Feng et. al., 2001). The agent technology allows software modules built to monitor, assist, and act on behalf of a user in order to inter-operate with other co-existing agents. It plays an increasing role in many e-Commerce applications (e.g. Lee and Liu, 2001; Liu and You, 2000).

This paper introduces a Web-based agent and it forms part of an advisory system for financial forecast. Much of the discussion will be devoted to the design and development of the framework and associated intelligent techniques. The agent architecture will conform to the intelligent iJADE model for easy integration (Lee and Liu, 2001). It will be convenient for small investors to access the advisory system tool via the Internet.

2. Background

Method for prediction includes the classical models (Kaufman, 1987) and the adaptive models (Kamijo and Tanigawa, 1990; Liu and Tang, 1997; Park and Han, 1995). The approach is based on analyzing price patterns and trading volume. It relies on the discovery of strong empirical regularities in observations of the system, the assumption being that any influences on stock prices are already reflected in the price movements. The application is primarily focused on identifying patterns that can indicate "when" to buy or sell based on market timing. There are problems in that regularities are not always evident, and are often masked by noise. Many financial anomalies therefore remain unexplainable. The classical models of this approach include the study of moving averages and regression indicators. They at best are capable of picking out trends in the stock market, but have difficulty in modeling cycles that are by no means repetitive in amplitude, period of shape.

As given in Liu (2001), the basic strategy used for analysing an investment is to:

- identify the long-term and short-term trends of the market
- identify the direction of these trends of the market
- identify how far along the market are these trends
- predict the turning points of the market
- predict the percentage change for different future time periods
- predict future tops and bottoms in the market
- predict points where stops should be placed
- develop direct buy and sell type signals

The following theories are considered as part of technical analysis for the study [5]. More details can be obtained from (e.g. John and Miller, 1996; Jun et al, 1993; Lui, 1990; Plummer, 1993).

Relative Strength Index (RSI)

The RSI is one of the most widely used technical indicators. It is highly effective in aiding a technical analyst in chart interpretation. Some factors to consider when using the index are:

- TOPS and BOTTOMS are indicated when the RSI goes above 70 or drops below 30.
- FAILURE SWINGS above 70 or below 30 on the RSI are strong indications of market reversals.
- SUPPORT and RESISTANCE often show up clearly on the RSI before becoming apparent on the bar chart.
- DIVERGENCE between the RSI and the price action on the chart is a very strong indicator that a market turning point is imminent.

The theoretical basis of Relative Strength Index is the momentum concept. A momentum oscillator is used to measure the velocity or rate of change of price over time. It is essentially a short-term trading indicator and also quite effective in extracting price information for a non-trending market. The Relative Strength Index Equation is

$$RSI = 100\left(1 - \frac{1}{1+RS}\right)$$

$$RS = \frac{Average\ of\ L\ day\ s\ close\ UP}{Average\ of\ L\ day\ s\ close\ DOWN}$$

where L is a variable which can be varied from 1 to 30. If the Average of L days close UP during the chosen time period is zero, the ratio RS is also assumed to be zero. However, if the Average of L days close DOWN is zero, RS is assumed to be equal to the Average of L days close UP. The ideal setting for Relative Strength is exactly one half the period of the cycle.

It has been suggested that levels of 70 and 30 respectively signify tops and bottoms. The index usually leads the market and peaks before the actual top or bottom. Extreme value such as 90 or 10 signifies unusual strength or weakness. Therefore, RSI can be used as an early warning signal.

Moving Average (MA)

Moving averages are calculated from historical price information. It represents a smoothing of actual price fluctuations. In flat or consolidating markets, moving averages would closely track the current prices. In trending markets, they can be used in buy and sell decision. A long-term trend indicator can be obtained by comparing a short-term moving average with a longer-term average. The trend is rising when the short term is above the longer term, and vice-versa. The buy signals tend to precede periods of increasing value in the stock price, while sell signals tend to precede periods of declining stock price.

The formulas for moving averages are as follows:

$$Exponential\,MovingAverage = \sum_{K=0}^{L-1} \frac{ClosingPrice}{\frac{b - b^{K}}{1-b}}$$

The smoothing gives a heavier weight to the most recent time periods and a lesser weight to earlier ones. If $\beta = 1.00$, then the average is a simple moving average.

$$Simple\ Moving\ Average = \frac{Sum\ of\ L\ day's\ ClosingPrice}{L}$$

Valid range for L = 1 to 200 (Default Setting = 20)

β = 0.0 to 1.0 (Default Setting = 1 and 0.75)

On Balance Volume (OBV)

OBV is a very popular indicator and is a running total of volume that reflects accumulation or distribution. Each day's volume is assigned a positive or negative value depending on whether prices closed higher or lower that day and a running total is kept by adding or subtracting the volume depending on the direction for the day. The direction of the OBV line is the thing to watch not the actual level. This indicator will often confirm underlying strength or weakness of a price trend and will often signal a top by declining while the stock is still rising, indicating big money is leaving the stock. Conversely, a rising OBV in the face of a declining price trend or an OBV that refuses to confirm a new stock reaction low could indicate smart money is moving in and a bottom may be at hand.

The mentioned indicators are commonly used by global professional financial advisors. Such analytical factors are very famous that most investors of every size of capital would make a deep reference on these before they make an investment decision. Usually, those indicators are not being referred to independently, but with mixed investigation that different combinations of those factors' situation. These combinations of indicator values will reflect many reasonable results of financial performance forecasting, which are not only in distinct level of prediction but possible in gradual, differential kind of results.

3. CBR Methodology

A learning system should make increasingly useful decisions as it accumulates experience. For case-based reasoning (CBR), the methodology can be effective even if the knowledge base is imperfect. Certain techniques of automated learning, such as explanation-based learning, work well only if a strong domain theory exists. In contrast, case reasoning can use many examples to overcome the gaps in a weak domain theory while still taking advantage of domain theory. CBR can also be used when the descriptions of the cases, as well as the domain theory, are incomplete. A further advantage of CBR is the relative ease of combining techniques with other approaches such as production rules. An example of such compatibility is a system which uses case reasoning to solve problems whenever possible.

In general, the prior cases retrieved by case reasoning will match the required solution only imperfectly. In particular, the source cases may fail to fulfill some of the requisite objectives.

3.1 Case Characteristics

The cases which we focus on are based on the characteristics of wave forms inside the track of the daily stock closing prices. In stock markets over the world, statistical histogram and line charts from the fluctuation of stock prices can provide some special meaningful, well-known wave propagation features. These kinds of wave propagations are defined as some signals, which are able to forecast the future conditions of the stock price movement. As each of these features describes a unique kind of current stock market atmosphere and also help forecast the future movement of the stock, we define them as independent cases in this study. Before the system can generate a new case, it has to make reference to the RULE class for the configuration of a case. Rule class contains the methods of figuring all aspects of sub cases and main cases. By changing the parameters in Rule class, the patterns of the same set of cases that the system can retrieve will be different. Therefore, cases are defined by the theory of wave features and their combinations.

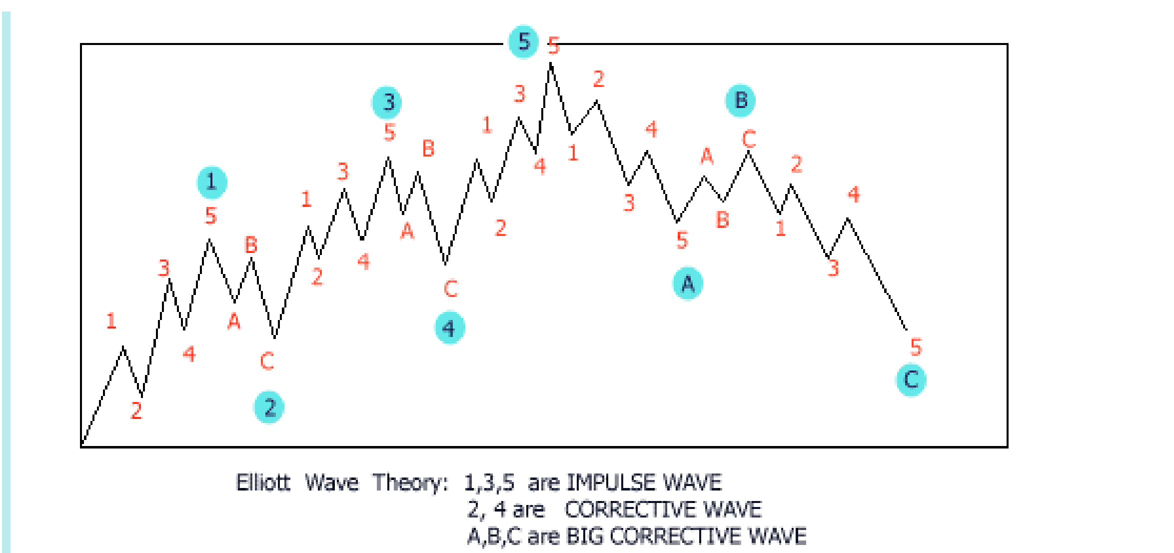


Fig. 1: Elliott Wave Theory

Such predicative wave combination features was firstly proposed by R. Elliott [4]. Nowadays, most of the stock traders still make a high rate of reference on his wave theory (Figure 1) to capture the events happened and catch the future trend of the stocks price. Elliott Theory explains about the impulse waves, corrective waves which are combined to form a middle to long term corrective waves.

Sharp rise / decline

When it is found during Feature recognizing process that, a wave's % Drop or % Rise is over the Tolerance value, a Feature of 'Sharp Rise' or 'Sharp Drop' will be recorded and stored in Case Database (Figures 2a-b). The 'Tolerance' in the system could be a constant value such that, whenever we need to adjust the degree of Rise/Drop that defined a Sharp Price Different, we can change the tolerance value.

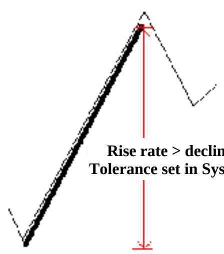


Fig. 2a: Sharp rise pattern

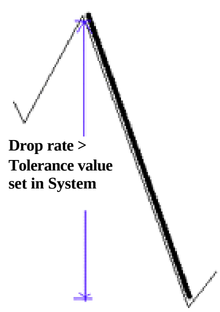


Fig. 2b: Sharp drop pattern

Rising / Declining Wedges

Wedge is the feature showing that the market is being stabilized and the amount of trading volume was being absorbed by the market, ready to approach a new, breaking Rise/ Drop outcome. Basically it is formed by 4 turning points with 2 opposite-angel lines, Wedges which show a rising propagation are named RISING WEDGE, while wedges showing a declining propagation are named as 'DECLINING WEDGE'. The dotted lines in Figures 3a-b are the possible breaking vector of the stock price in the short-term future. As the breaking period starts, the trading also increases.

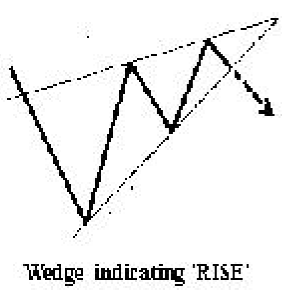


Fig. 3a: Rising wedge

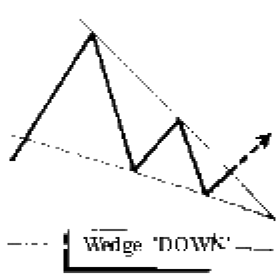


Fig. 3b: Declining wedge

Shoulder and Head

A head and shoulders reversal pattern forms after an uptrend, and its completion marks a trend reversal. The pattern contains three successive peaks with the middle peak (head) being the highest and the two outside peaks (shoulders) being low and roughly equal. The reaction lows of each peak can be connected to form support, or a neckline (e.g. Figure 4).

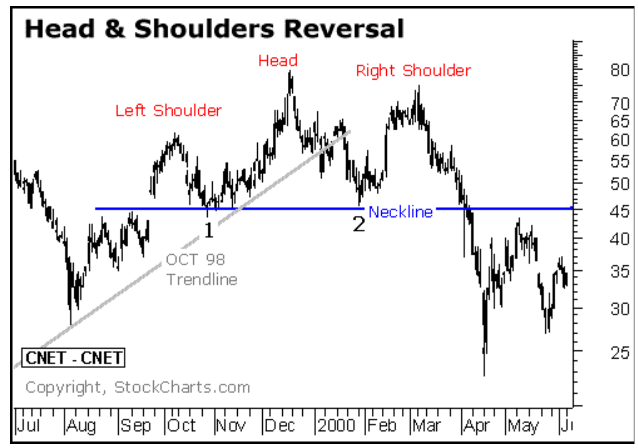


Fig. 4: Head and shoulders top marking trend reversal

On the other hand, the head and shoulders bottom is sometimes referred to as an inverse head and shoulders. The pattern shares many common characteristics with its comparable partner, but relies more on volume patterns for confirmation. As a major reversal pattern, the head and shoulders bottom forms after a downtrend, and its completion marks a change in trend. The pattern contains three successive troughs with the middle trough (head) being the deepest and the two outside troughs (shoulders) being shallower. Ideally, the two shoulders would be equal in height and width. The reaction highs in the middle of the pattern can be connected to form resistance, or a neckline (e.g. Figure 5).

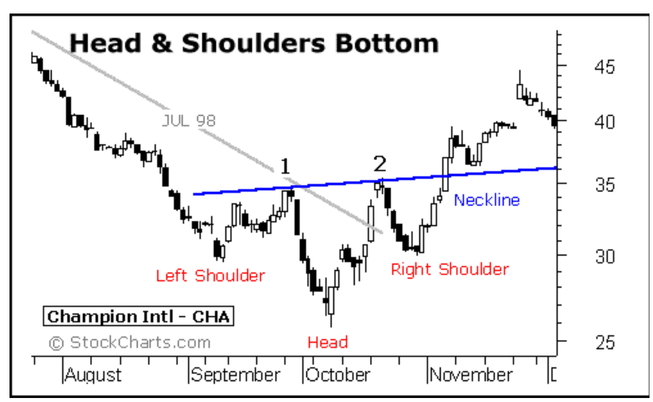


Fig. 5: Head and shoulders bottom showing trend reversal

Stock Crisis (Bear Stock Moving)

For an initial study of common bear market's moving habits, it was found that before a stock crisis took place, usually there was a substantial high record of trading volume, implying that a mass amount of monetary asset had been injected into the stock market. At the same moment, however, the market doesn't result into a big rise by such sharp amount of buying action - this also implies that from another side, there was an equal-size flowing out of money trading out from the stock market. As large volume has been traded in, but the pay back doesn't show in short term stock price trendy, short term capitals drain away first, and give out a first wave of significant decline of price. For the optimistic market, this declination would be quickly absorbed by the market and Rising Wedge would return shortly. However, since the last Declination accumulated a comparatively high amount of 'losing' capital, and those capital would flow away at this Rise in order to cut off their potential further loss, this scenario leads to the second time of Price Declination (see Figure 6).

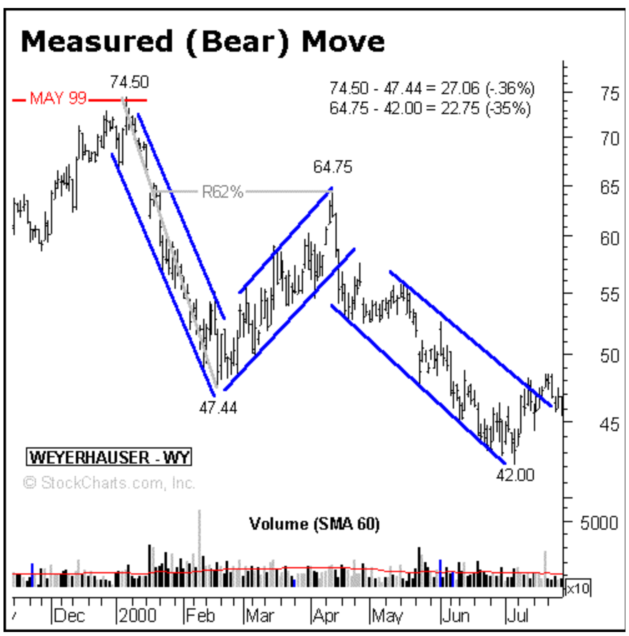


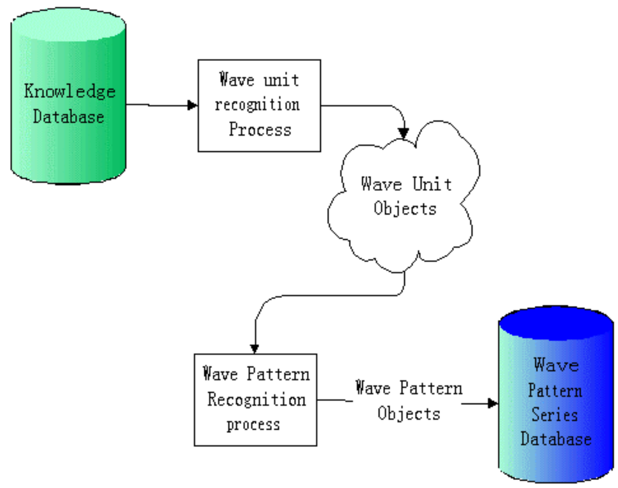
Fig. 6: Bear stock moving

This buy and sell action will return repeatedly in cycle, and the attitude of the stock market will gradually changed from optimistic to pessimistic. Volume of leaving capital will become larger, and finally, most capital would be rushing out from the market, and record a substantial fatal price drop.

3.2 Case Identification by CBR Agent

The stock price trading data is collected from the Datastream International System which is the online database providing comprehensive current and, historical coverage on over 140,000 securities and instruments from markets worldwide. In this study, 33 stock data got involved and every stock contains about 2-10 years records from Jan 1990- Feb 2001.

As indicated in Figure 7, when the knowledge database is formed, the CBR module needs to make use of the analysis indicators with respect to the dates in knowledge database



and to construct wave-unit based data objects, extracting every feature of the wave patterns defined by the Definition Rules System.

Fig. 7: Agent transformation from knowledge data to Wave Pattern Objects

Wave units recognition

The knowledge database consists of daily stock high/low/close prices with analysis indicators such as RSIs, moving averages of price, and corresponding trading volume. The wave recognition program makes reference to a constant period of successive prices. Within this period, two comparative minimum prices and a maximum price are found. These 3 points are then classified into a unit of 'wave', and its start and end date, average RSI, volume and price will also be calculated right after the wave unit has been found (Figure 8). The chain of wave units will not be stored into the Database table, but settled in memory arrays to wait for the next step of Case generation process - Waves Pattern Feature Capture Process.

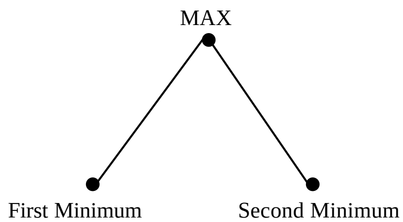


Fig. 8: A Wave unit

Wave pattern feature capturing process

A class program is provided to allow the system to capture any existence of wave patterns form on the stock price charts. The rules which are used to define the features of each pattern are written in the Rule_Wave.java program. This rule program is set up with several constraints for the wave units, testing whether the units are adapted to the conditions by these constraints, and a relational data set will be formulated after testing those wave units. These rules will be run by the system program after all the wave units are recognized. The wave units will be parsed into the Rules class (Figure 9). The class will read through each of the wave unit, with reference to their maximum and minimum price levels, and compared with their neighbors. Under the comparisons between those successive wave units, the rules could collect the required relationship and finally figure out the defined Wave chart patterns which are present within the knowledge data set. The pattern information such as its start and end date, ***turnover*** and ***over-limit*** condition on *RSI*, and *Volumes* and *Prices* Moving *Average* are also kept in the Pattern database.

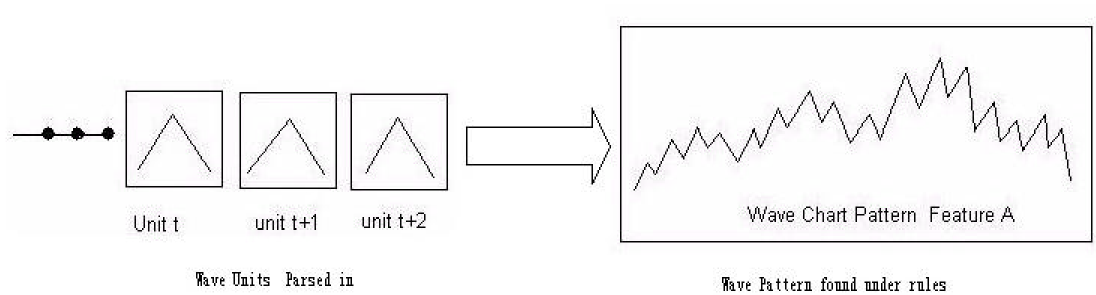


Figure 9: Wave units are recognized and transformed into one feature pattern object

Revise and Learning

After all the wave patterns have been captured and kept in the database, the system starts to process the revise and learning parts. Revise means that the system retrieves the updated stock data and converts them into case knowledge, then study the new current status of the cases and appends the new result set into the result database which is for users' direct query. The system was set to refer to **3 Successive Cases** within a series of stock cases as one complete CASE for prediction purpose.

As shown in Figure 10, given the stock price P(t) at time t, the system will examine the stock prices during the period between (t-200) and (t-1). It will compare these historical stock prices with the current one to decide whether P(t+n) is higher than, equal or lower than P(t).

The Revise System will update the result in the reference table and extract the maximum and minimum rates of the ***future rise*** and ***future drop*** of the stock, with respect to long term and short term forecast. The system also works out information about the frequency of occurrences of future RISE, future DROP, the maximum and minimum rate of RISE and DROP, the 'turnover' and 'over the top' status of stock volume, price averages, as well as the next coming wave pattern. The classifications of these patterns are given in Table 1. The fact that if all the combinations of sub-cases are covered, there will be over 3,000,000 case records stored in the database! In this CBR project, most of the sub-case do not mainly to indicate an actual price or value in the financial (stock) price but a comparative situation of a chosen observing scene such as the over / below support average, standard financial indictors/price turnover occurrence, trading volume comparative level. Therefore, relational data set and database infrastructure is selected for major data reference in its DB system.

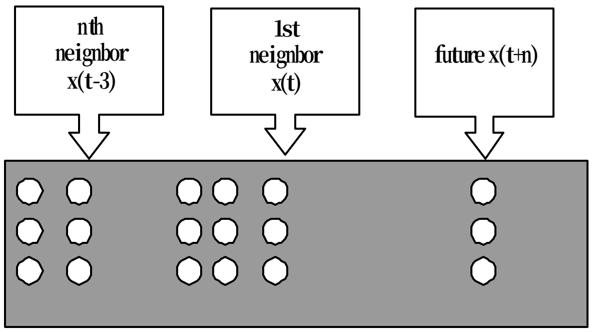


Fig. 10: The study of cases in the nearest neighborhood

For a formation of a full case, which is to be recognized and referred from the same case occurrence in the past history, which is a combination of sub-cases, each of which independently are the relational data indicators mentioned in last session.

In this proposed system, Revise process is described as, in more meaningful and understandable way, a discrete 'same case' performance's past history reference. Firstly, revise process targets to the current existing case figuration. The relational data set, which was collected in the previous knowledge generation process is picked up and combined together to form a current 'full case' which will be used for further history reference. Then, the process would be connected to the case performance library to match out the case similar to the current 'full case', and then retrieve its corresponding performance indicating parameters concluded from this full case's past occurring result.

Besides revision of past performance, also the system is proposed to be capable of making a study on most recent financial trendy effectiveness, implicit indication of nowadays investors sight direction to the case occurrence, and their decision to this case as well as optional habits. The proposed system would adjust the conclusion of past performance after this study. This is what we called the ability 'feasibility to case occurrence up-to-date'. Learning process is designed to take over this ability process.

Every time the existing case is extracted and its actual result's relational data set have been reflected from the market for a period after the current case has passed, this result set will be instantly accumulated to the past performance database over the current performance, so as to make a newly concluded 'full case' performance result record stored in. Since new direction, depth of case effectiveness to the change, new price/change percentage boundaries are updated to the record, the system would then be able to know the new trend of the market to the recorded case. Therefore, next time when this similar case happened and the system directed to that case for performance result query, the system could get a result comparatively more adhesive to the unstable market!

Pattern Type	Pattern signal stored in table
Elloitt Wave	3_WaveSet
Sharp Rise	Sharp_Rise
Sharp Drop	Sharp_Drop
Decline Wedge Set	MultiW_Drop
Rise Wedge Set	MultiW_Rise
Shoulder	Shoulder
Stock Crisis	= Crisis =

Table 1: Classification of case patterns

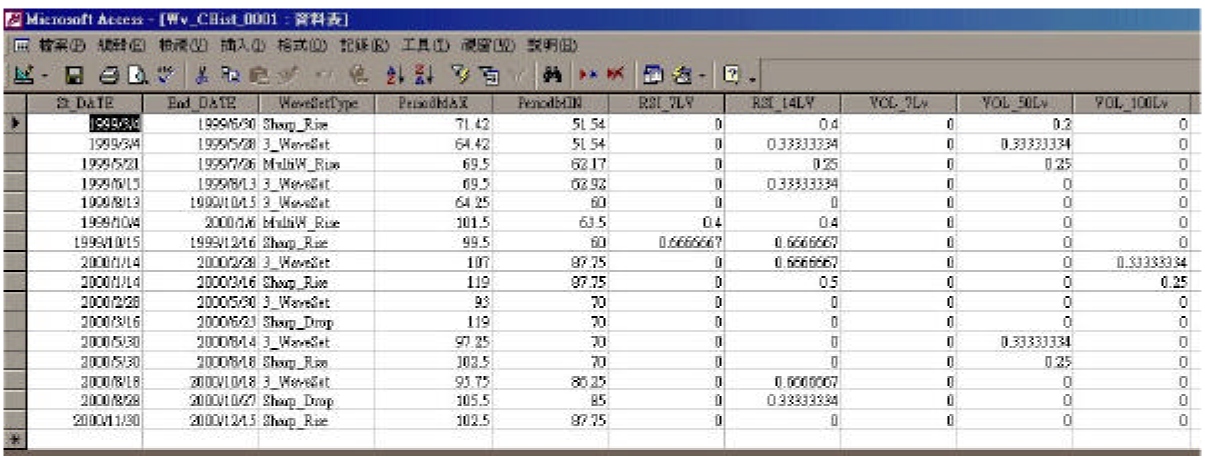
4. Experimental Results and Analysis

The basic flow for the Web-based CBR agent system consists of the following:

1. Client (the Web browsing agent) makes a HTTP request (Figure 11).
2. When Web Server receives the request it will forward the request to the back-end server program (Java Servlet Class running in server). If the back-end program has not been started, the web server will load it into the Java Virtual Machine (JVM) and execute it.
3. After the back-end program has received the HTTP request it will perform data analysis, case identification and generation (Figures 12-14). The system is connected to the Database by JDBC to access the data.
4. When the corresponding processes are finished, the back-end server program will return a message to the Web server.
5. The response with forecasting results will be forwarded back to the Client browser (Figure 15).

Figures 12-14 give an overview of the prediction result by the CBR stock prediction system. Since the database used by the current system contains insufficiently 3 years stock price and volume daily records, which is still a distance to the recommended least acceptable size of 5 years record of it, the results listed are of a level for initial reference only, instead of a confident demonstration of CBR forecasting system's accuracy. The most highlighted side by this table is the format of it's presentation. By using CBR prediction system, the sub-case can be used for explaining to customers/ investors the result with understandable reasons with different market situation description. This factor of presentation is only available under case based reasoning prediction system apart from other model such as Neural Networks. Customers want the accurate result, but also they want to know what are the supporting factors behind this result, which are very important for encourage them to make a trust to the prediction! Besides, as CBR methodology is mainly making use of sub-case combination under a agreed standard format, the CBR prediction structure and result/ reason options could be easily expanded to a wider forecasting area by adding new combing sub-case to the 'full case' formation standard, as well as providing new add-on to prediction result set such as political support sentences, next coming chart pattern(s). For development side consideration, it is more easily to expand.

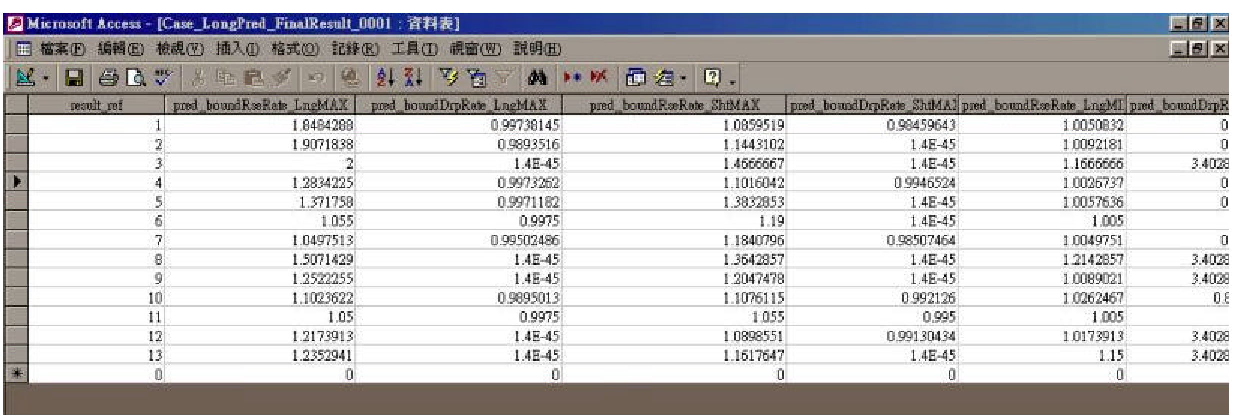
Fig. 11: Options for Input prediction request



Microsoft Access - [Wv_CHist_0001 : 資料表]

St_DATE	End_DATE	WaveSetType	PeriodMAX	PeriodMIN	RSI_7LV	RSI_14LV	VOL_7Lv	VOL_50Lv	VOL_100Lv
[illegible]	1999/6/30	Sharp_Rise	71.42	51.54	0	0.4	0	0.2	0
1999/3/4	1999/5/28	3_WaveSet	64.42	51.54	0	0.33333334	0	0.33333334	0
1999/5/21	1999/7/26	MultiW_Rise	69.5	62.17	0	0.25	0	0.25	0
1999/6/15	1999/8/13	3_WaveSet	69.5	62.92	0	0.33333334	0	0	0
1999/8/13	1999/10/15	3_WaveSet	64.25	60	0	0	0	0	0
1999/10/4	2000/1/6	MultiW_Rise	101.5	63.5	0.4	0.4	0	0	0
1999/10/15	1999/12/16	Sharp_Rise	99.5	60	0.6666667	0.6666667	0	0	0
2000/1/14	2000/2/28	3_WaveSet	107	87.75	0	0.6666667	0	0	0.33333334
2000/1/14	2000/3/16	Sharp_Rise	119	87.75	0	0.5	0	0	0.25
2000/2/28	2000/5/30	3_WaveSet	93	70	0	0	0	0	0
2000/3/16	2000/6/23	Sharp_Drop	119	70	0	0	0	0	0
2000/5/30	2000/8/14	3_WaveSet	97.25	70	0	0	0	0.33333334	0
2000/5/30	2000/8/18	Sharp_Rise	103.5	70	0	0	0	0.25	0
2000/8/18	2000/10/18	3_WaveSet	95.75	86.25	0	0.6666667	0	0	0
2000/8/28	2000/10/27	Sharp_Drop	105.5	85	0	0.33333334	0	0	0
2000/11/30	2000/12/15	Sharp_Rise	102.5	87.75	0	0	0	0	0

Fig. 12: Sample cases collected in the Web-based system (e.g. stock 0001 indicates Cheung Kong Holdings)



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result_ref	pred_boundRseRate_LngMAX	pred_boundDrpRate_LngMAX	pred_boundRseRate_ShtMAX	pred_boundDrpRate_ShtMAX	pred_boundRseRate_LngMI	pred_boundDrpR
1	1.8484288	0.99738145	1.0859519	0.98459643	1.0050832	0
2	1.9071838	0.9893516	1.1443102	1.4E-45	1.0092181	0
3	2	1.4E-45	1.4666667	1.4E-45	1.1666666	3.4028
4	1.2834225	0.9973262	1.1016042	0.9946524	1.0026737	0
5	1.371758	0.9971182	1.3832853	1.4E-45	1.0057636	0
6	1.055	0.9975	1.19	1.4E-45	1.005	
7	1.0497513	0.99502486	1.1840796	0.98507464	1.0049751	0
8	1.5071429	1.4E-45	1.3642857	1.4E-45	1.2142857	3.4028
9	1.2522255	1.4E-45	1.2047478	1.4E-45	1.0089021	3.4028
10	1.1023622	0.9895013	1.1076115	0.992126	1.0262467	0.8
11	1.05	0.9975	1.055	0.995	1.005	
12	1.2173913	1.4E-45	1.0898551	0.99130434	1.0173913	3.4028
13	1.2352941	1.4E-45	1.1617647	1.4E-45	1.15	3.4028
0	0	0	0	0	0	

Fig. 13: Case Performance history table generated after the Revise process

	Plan		Term			Result	Current Case		
Stock Code	Reserve	Aggressive	Long	Short	Advice	Bound Rate of Change after 30 days	First (most near)	Second	Third
0001	O		O		BUY	1.15%	Sharp Rise	Elloitt Wave	Sharp Drop
0001		O	O		BUY	1.24%	Sharp Rise	Elloitt Wave	Sharp Drop
0001	O			O	BUY	1.03%	Sharp Rise	Elloitt Wave	Sharp Drop
0001		O		O	BUY	1.16%	Sharp Rise	Elloitt Wave	Sharp Drop
0002	O		O		BUY	0.44%	Rise Wedge	Sharp Drop	Drop Wedge
0002		O	O		BUY	4.21%	Rise Wedge	Sharp Drop	Drop Wedge
0002	O			O	BUY	0.12%	Rise Wedge	Sharp Drop	Drop Wedge
0002		O		O	BUY	2.56%	Rise Wedge	Sharp Drop	Drop Wedge
0003	O		O		BUY	0.50%	Elloitt Wave	Sharp Rise	Rise Wedge
0003		O	O		BUY	4.50%	Elloitt Wave	Sharp Rise	Rise Wedge
0003	O			O	SELL	1.30%	Elloitt Wave	Sharp Rise	Rise Wedge
0003		O		O	SELL	0.13%	Elloitt Wave	Sharp Rise	Rise Wedge
0004	O		O		BUY	0.44%	Rise Wedge	Sharp Rise	Sharp Drop
0004		O	O		BUY	2.21%	Rise Wedge	Sharp Rise	Sharp Drop
0004	O			O	BUY	0.12%	Rise Wedge	Sharp Rise	Sharp Drop
0004		O		O	BUY	1.54%	Rise Wedge	Sharp Rise	Sharp Drop
0005	O		O		HOLD	-	Rise Wedge	Sharp Rise	Sharp Rise
0005		O	O		HOLD	-	Rise Wedge	Sharp Rise	Sharp Rise
0005	O			O	HOLD	-	Rise Wedge	Sharp Rise	Sharp Rise
0005		O		O	HOLD	-	Rise Wedge	Sharp Rise	Sharp Rise
0006	O		O		BUY	0.93%	Elloitt Wave	Elloitt Wave	Elloitt Wave
0006		O	O		BUY	5.35%	Elloitt Wave	Elloitt Wave	Elloitt Wave
0006	O			O	BUY	2.44%	Elloitt Wave	Elloitt Wave	Elloitt Wave
0006		O		O	BUY	2.13%	Elloitt Wave	Elloitt Wave	Elloitt Wave
0008	O		O		SELL	5.44%	Sharp Drop	Drop Wedge	Sharp Rise
0008		O	O		SELL	2.90%	Sharp Drop	Drop Wedge	Sharp Rise
0008	O			O	BUY	1.63%	Sharp Drop	Drop Wedge	Sharp Rise
0008		O		O	BUY	3.32%	Sharp Drop	Drop Wedge	Sharp Rise

Fig. 14: Sample prediction result overview (Data period: 01 Jan 1999 – 15 Feb 2001)

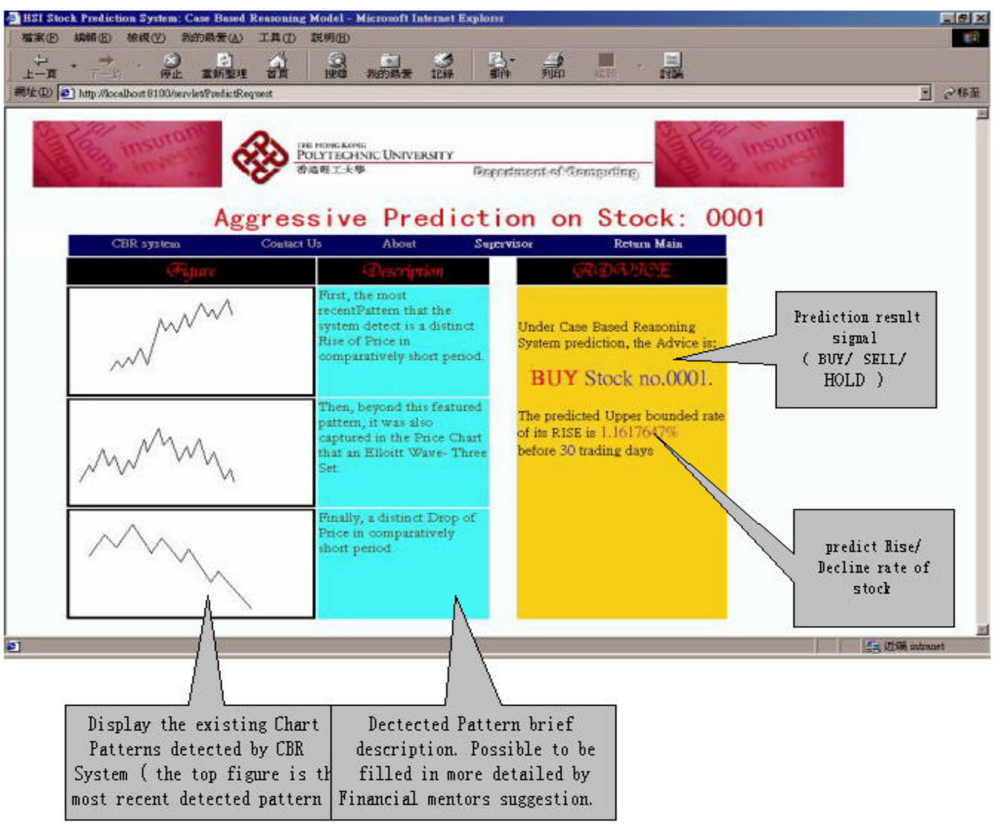

Fig. 15: Sample screen displaying the prediction result

5. Discussion

Preliminary result indicates that the CBR agent model is promising and reasonable. The case type it captured is the

Stock Pattern derived from the chart, which is also being observed by the experienced professional investors in stock markets. They have a common knowledge and restricted reaction to those happenings of stock patterns. For example, for every 5th little wave among the several rising little waves, by Elliott Wave Theory, they will regard it as a 'turning wave' that would nearly be certain that the price will drop after the completion of that wave, therefore, they would most likely sell stock and hence make the price really recording a 'Drop'.

In addition, the system is feasible to capture the trading behavior of the market with expandable case options. Among the products of AI prediction models, they mainly refer to the statistical analysis on stocks' price trendy and learning about the result possibly, this approach would be commented by the financial investors that the model sounds biased to rely on statistical theory, but not the real financial situation. Financial markets investors will observe the pattern occurred in the latest chart reports and consider them by past experience that the stock would drop or rise in the short or long distance future. The design of this CBR model follows such approach, and be able to capture the investors' habits of buying/selling stocks. It is also adaptive in the sense that the experience of buying/selling actions of investors will be adjusted or even changed. Such type of amendment is also available by CBR prediction model.

6. Conclusion and Future Work

The Web-based CBR agent model is used for financial stock forecasting. It supports Knowledge generation process, Wave units mining process and Wave Pattern recognition process, and Case Revise and Learning process which can be accessed offline. The data set is of analytical data type, and Case Base data sets are mainly relational data type in the knowledge base. This CBR system mainly refers to the Patterns combination as Reference case. In addition, other analytical relational data such as Volume, RSI, Moving average of Price are also considered as important components making up the Wave pattern cases.

The CBR agent model in this process was written in Server- Client interactive Java Servlet for Web environment application. Therefore people can easily access the CBR stock prediction system by browsing into the system interface through Internet. According to the experimental results, it was found that the CBR prediction is reliable in financial forecasting, especially for long term prediction.

The system has been developed having some basic functions of case capturing, analytical indexes involvomg study and revise process. To further the development, it can be expanded by plugging in more types of patterns knowledge on advices from financial authorities and professionals.

As CBR can also capture the habits of *Next Case prediction*, it is possible that the prediction can provide not only the trend signal, Rise/ Drop rate, but also some detailed future movement of stock, i.e. which pattern the stock will likely to develop, and its formation could also be pre-processed, and further displayed as part of the output. It can be more logical with reasons and easily understood and trusted by users.

In this paper, it was chosen that wave pattern and analytical data status be used for case classification and stock forecast. Due to the fact that, for a complete formation of a wave pattern, it requires quite a long period of data and consequently, in order to collect a satisfactory amount of past cases for past performance reference, the system needs to be fed with a longer period of stock price data (e.g. 10 years) to be able to keep track of those longer cycles of events. Besides, sometimes the system cannot capture a new short-term pattern case if the latest stock data do not form a distinct pattern quickly enough. This will affect the short-term prediction process. In future, it is certainly possible that more determining factors can be added into the case capture for decision-making. New factors such as political, micro-economics situation, macro-economics situation, movement of funds, views of financial mentors…etc can be taken into consideration for further development.

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